Interactive Parameter Sensitivity Visualization and Exploration for DTI Fiber Tracking

Category: Research

Abstract— Fiber tracking of Diffusion Tensor Imaging (DTI) data is a useful technique to explore and analyze anatomical connectivity in living brain. However, most fiber tracking algorithms demand a plenty of user defined parameters which is a major source of uncertainty.

Index Terms—Parameter Analysis, Fiber Tracking, Sensitivity Visualization, Uncertainty Visualization.

1 Introduction

The introduction...

2 Problem Statement

Description about the problem...

3 Related Work

The related work...

4 Pipeline Overview

In order to study how parameter variations influence the tracking results. We design a two-stage visualization and exploration system as illustrated in Figure 1. In the processing stage, we start by a uniform sampling in the parameter space to generate a sequence of tracking configurations. With these configurations, a set of fiber models are extracted. To provide the user with information about the variations among fiber models, a unique signature for each fiber model is produced through a cluster-projection routine. At last, a non-linear projection technique is employed to build a low-dimensional embedding for all signatures. This embedding constitutes a basis for further exploration and analysis. In the visual exploration stage, a suit of useful tools including linked views and interaction widgets are provided.

4.1 Generating Fiber Models

The high computational costs of fiber tracking algorithms severely constrain the ability to interactively explore how small variations in parameter space affect the output tracking. In order to release the cumbersome trial-and-error process of changing configurations in the parameter space, waiting for computation, and then exploring the output tracking to gain insight of variations, we uniformly sample the parameter space in an offline process to generate a set of fiber models. At a first look, this may seem costly in terms of processing time and resources. However, this process can be performed ”over night” such that the user can devote his/her attention to other matters.

Since our work aims at exploring the pairwise sensitivity of tracking parameters, given a set of parameters $P = \{p_1, p_2, ..., p_m\}$, we restrict the sampling space $\mathbb{S}$ into a subspace of $\mathbb{R}^m$ by selecting a pair of parameters of interest p_i, p_j ($i < j$) and letting all other parameters to be fixed values. Then, we generate number of n samples from $\mathbb{S}$. We refer to each sample as a *configuration vector* $\mathbf{c} \in \mathbb{S}$. By leveraging a fully-featured toolkit called Camino [3], a set of fiber models $M = \{M_i, i = 1, 2, ..., n\}$ are produced with a sequence of configurations $C = \{c_1, c_2, ..., c_n\}$. Each fiber model $M_i = \{f_{ij}, j = 1, 2, ..., n_i\}$ consists of n_i fibers, where f_{ij} is a fiber. Note that no post-processing (e.g. length filtering) for fibers are performed during this process. Thus, all fiber models have the same number of fibers which are equal to the number of seed points.

4.2 Structuring Signature Database

Generally, a fiber model consists of thousands of fibers, and each of them can be regarded as a high-dimensional point in the fiber space. If we visualize such complex fiber model with streamlines or streamtubes in their native 3D space, the visual clutter issues may be created, which are great obstacles for users to inspect variations introduced by parameter perturbations. To provide the user with information about the variations among DTI fiber models, we propose a projection based method to create a unique 2D signature for each fiber model M_i. The new representation of each fiber model does not suffer from visual clutter issue.

4.2.1 Preprocessing

Typically, the number of vertices in each fiber f_{ij} of a fiber model M_i are not identical. In other words, all fibers are not in the same dimensional space. However, many processes which will be described in the following sections require that the input data have the same dimensionality. Accordingly, we perform an arc-length parameterization for each fiber, and equally subdivide the fiber into a fixed number N_p of segments. The number N_p is the maximum number of vertices in any fiber of the model. Generally, the number ranges from 200 to 250 in our experiments.

Because our approach rests on a projection routine, it is required to calculate the similarities between each pair of fibers. Currently, manly distance based techniques [2, 9] can be employed. However, most of them are quite time-consuming. Rather than calculating similarities in fiber space, we se the Eauclidean distance in a feature space as a metric for similarities between fibers. Similar to [7], our feature space is also composed by the spatial features and shape features of fibers. The spatial feature of a fiber incudes the star point, the end point, the center of mass, and the fiber length. The shape feature of a fiber is comprised of the Fourier low-frequency coefficients [6, 4] of each dimension. More specifically, a 1D DFT is applied to the x-coordinate sequence, y-coordinate sequence, and z-coordinate sequence of a fiber individually. Because the coefficients have imagine part, we only use magnitudes of the first 15 low-frequency coefficients of each dimension as our shape feature descriptor in our experiments. For example, given a fiber of 200 vertices, a 55-dimensional feature vector (10 from the spatial feature descriptor and 45 from the shape feature descriptor) can be obtained. We denote by f^*_{ij} the feature vector of fiber f_{ij} and $M^* = \{M^*_i, i = 1, 2, ..., n\}$ the feature models of fiber model M.

4.2.2 Tow-Phase Embedding

Multidimensional projection has been demonstrated to be a useful technique for exploring DTI fibers [2, 7]. However, most MP techniques use a single global mapping to project the data instances from a high-dimensional space to a visual space. In a sense, the global nature means more computational resources needed and few user intervention allowed during projection.

In our work, we employ a two-phase projection scheme to project the feature vectors into the visual space. In the first phase, we compute a set of representative feature vectors from a batch of feature models randomly selected from M^*. For simplicity, we use k-medoids algorithm to cluster the selected feature vectors into groups and take

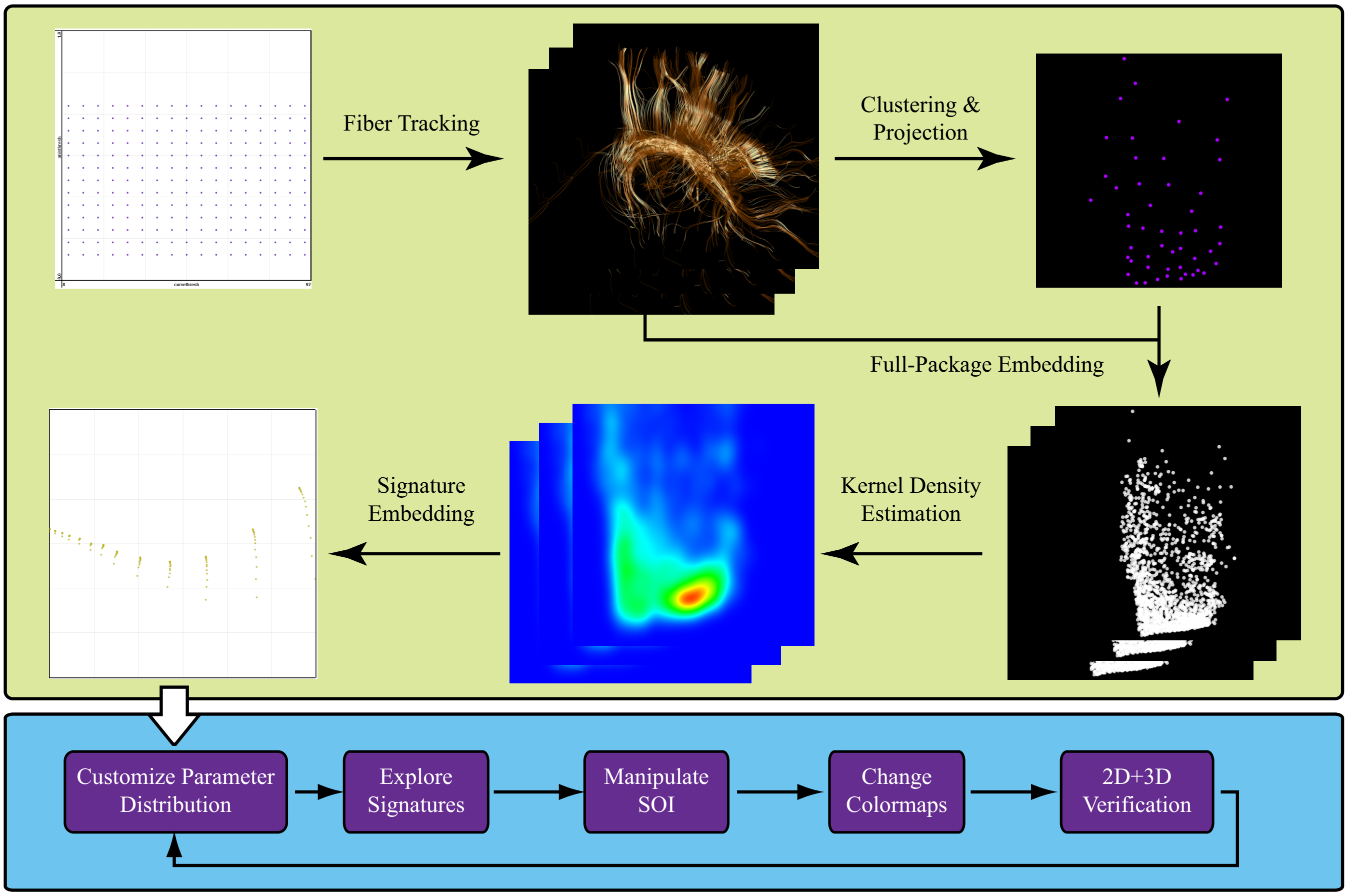

Fig. 1. The schematic pipeline overview.

the cluster centers as representative feature vectors. Then, a fast and precise multidimensional scaling (MDS) [1] technique is adopted to project these vectors into a 2D space. In fact, the resulting projection in the first phase constitutes a skeleton of the final projection for each feature model. In the second phase, we employ the *Local Affine Multidimensional Projection (LAMP)* [5] to project each feature model. Compared with many projection approaches, *LAMP* can obtain a better tradeoff between the computational performance and accuracy. Finally, we use the resulting projection of feature model as the low-dimensional embedding of the corresponding fiber model.

4.2.3 Kernel Density Estimation

The embedding yields a scatterplot of discrete 2D points. To facilitate recognition and visualization, we further apply a nearest neighbor kernel density estimation (KDE) technique with the Gaussian kernel [8] to the scatterplot, yielding a continuous 2D map. Each element of the map records a density.

Thus, each fiber model uniquely determines a signature map: a discrete scatterplot associated with a continuous KDE map.

4.3 Signature Embedding

As described above, each fiber model in M is encoded with a continuous 2D KDE map which can be regarded as a high-dimensional point by aligning it into a 1D array, and its relationship to other fiber models are non-linear. Therefore, a non-linear dimension reduction technique is needed to gain the low-dimensional manifold within signatures. The Locally Linear Embedding (LLE) technique meets our requirements. It has several advantages over many other techniques, including faster optimization by taking advantage of sparse matrix algorithms and better results. LLE first constructs a k-neighborhood connection graph based on the specified similarity measure. Here, we use the Euclidean distance to measure the similarity between two KDE maps. Then, it computes the weights for low-dimensional representation by minimizing the reconstruction error through a cost function:

$$\varepsilon(Y) = \sum_{i=1}^{n} |y_i - \sum_{j=1}^{k} w_i y_{ij}|^2 \tag{1}$$

where y_i is the 1D array of a KDE map, y_{ij} denotes its neighbors, and w_i corresponds to the embedding weights.

5 Visual Exploration

6 Results and Analysis

Results...

7 Conclusions

Conclusions...

References

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